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Abstract

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JEL Classification: D44, D82, D83

Keywords: Data, Advertising, Competition, Auctions, Matching

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Managed Campaigns and Data-Augmented Auctions for Digital Advertising

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April 17, 2023

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1 Introduction

1.1 Motivation and Results

Digital advertising facilitates the matching of consumers and advertisers online. Advertisers join digital platforms to reach a wider audience for their products, but must balance several competing objectives. Digital platforms allow advertisers to reach a broader spectrum of potential shoppers beyond their loyal customers. As platforms mediate commerce for many advertisers, products, and consumers, they gather data that can help improve the matches formed on the platform. However, the service provided by the platforms is costly, so advertisers must balance interacting with their loyal customers off the platform with gaining shoppers on the platform. As shoppers can take advantage of offers on and off the platform, advertisers face a “showrooming” constraint: they must ensure their offer on the platform is weakly better than the off-platform offer to complete the match on the platform.¹

In this paper, we develop an auction model that takes into account these three fundamental aspects of digital advertising. First, advertisers can reach at least a fraction of their customers outside of the platforms, either through an offline presence such as stores, or their own online presence, or through other third parties that list their offers. Second, the platform collects information from many similar items, viewers, and bidders, and therefore can improve the efficiency of the matching on the platform. Third, the matching of viewers and advertisers on the platform is governed by bidding mechanisms.

Commonly, digital platforms organize the competition for attention among the advertisers through an auction-based allocation mechanism. As the market for digital advertising has expanded and become more complex, digital platforms and other advertising intermediaries often implement bidding for advertising opportunities on behalf of the advertisers. These intermediaries then run managed campaigns for advertisers by choosing how to bid across many opportunities to create matches. These managed campaigns are implemented through auto-bidding algorithms that bid on behalf of the advertisers with certain objectives and relevant constraints explicitly stated.²

¹In the context of advertising platforms, where the matching fee is typically incurred before the transaction, either in the form of pay-per-impression or pay-per-click fees, the advertiser faces the showrooming constraint directly. The advertiser wants to pay for the listing if and only if it generates the sale. The offline transaction could have occurred without the advertising. In other platforms where the fee is transaction-based, such as a referral fee on shopping services such as Amazon, the showrooming constraint is often imposed by the platform in the form of most favored nation clause, i.e., the advertiser commits to offer the most favorable price online.

²A recent literature has developed around autobidding algorithms when the bidders formulate their objective outside of the class of quasilinear utility models in mechanism design. For example, the bidder

We begin the analysis with a second-price auction for a single advertising slot. Here, the platform augments the information of the bidder and solicits a bid for each estimated match value between consumer and advertiser. We refer to this as data-augmented bidding. Each advertiser can offer a bid for the slot and a price at which it offers the product associated with the advertising slot. Simultaneously, each advertiser has to choose the price at which it offers its product to the *loyal customers* off the platform customers. The available data online improves the quality of matches online. The *shoppers* on the platform are not loyal and choose to buy the product that offers them the highest net value. Off the platform, the advertisers do not have access to the data of the platform and offer a uniform price to the loyal customers. At this price, some customers will receive an information rent, namely those with values above the product price. Customers with values below the product prices will be priced out of the market.

With the additional data of the platform, the advertiser can offer prices that reflect the willingness-to-pay of the customers. This form of third-degree price discrimination on the platform serves to broaden the market and helps to create a more efficient allocation. Thus, the advertiser is using the additional information to reach more shoppers and improve the matches formed on the platform. Concurrently, the advertiser seeks to relax the showrooming constraint from the off-platform market to compete more fiercely on the platform. We are particularly interested in how data-augmented bidding impacts the welfare both on and off the platform.

We derive the optimal bidding and pricing strategy of the advertisers (Theorem 1). On the platform, the second-price auction implements an efficient allocation, and the additional data allows the advertiser to sell successfully to consumers with lower values without the need to price them out of the market (Proposition 1). Off the platform, the advertisers raise their price to their loyal customers relative to the price they would have charged in a stand-alone market (Proposition 2). By making their product only available at a higher price, each advertiser can weaken the showrooming constraint and compete more vigorously on the platform. The off-platform prices increase with the number of on-platform shoppers (Proposition 3) and decrease with the number of bidders (Proposition 4). Finally, as bidders are homogeneous ex ante, the platform can impose a participation fee that extracts all their surplus without affecting the subsequent prices and bids (Proposition 5).

We then introduce the notion of an *independent managed campaign*. In this more centralized mechanism, the platform proposes to each advertiser an advertising budget, an

may seek to maximize return on investments and have budget or spending constraints.

autobidding algorithm, and pricing function for the product on the platform. The autobidding algorithm governs how the managed campaign for every advertiser bids for potential matches as a function of the value of the match. Each advertiser simultaneously decides whether to enter into the managed campaign or not, and how to price its product off the platform.³ Here, we restrict the platform’s pricing policy only to price based on the consumer’s value for the advertiser’s own product, and not on the consumer’s value for other advertisers’ products.

The optimal independent managed campaign mechanism implements an efficient allocation of advertising slots (Proposition 6), but relative to either a second-price auction or even a revenue optimal auction design, it differs along a number of dimensions that have substantial impact on the outcomes (Theorem 2). First, by charging the bidders up front for expected matches, the digital platform can capture a larger share of the surplus yet do so without hurting the efficiency of the allocation. Under a sufficient condition on the value distribution, the off-platform posted prices are lower than the stand-alone monopoly prices (Proposition 7). Thus, the equilibrium outcome with the managed campaign can lead to a more efficient outcome both on- and off-platform.

We finally introduce the notion of a *sophisticated managed campaign*, where the pricing policy offered by the platform can condition on the full vector of values of each consumer. In this case, we show that the platform optimizes its revenue by offering best-value pricing; that is, the platform implements the efficient allocation, but ensures that the efficient firm always makes the offer with the best value to the consumer (Theorem 3). However, in doing so, the platform weakens competition, and so the firms raise their posted prices off the platform in order to extract more surplus from the online consumers. We show that under a relatively mild condition, posted prices are lowest with an independent managed campaign, followed by data-augmented bidding (Theorem 5). Posted prices are always highest with a sophisticated managed campaign (Theorem 6).

The implications of managed campaigns for the platform revenue are more nuanced. The sophisticated managed campaign allows the platform to reproduce the outcome of any independent managed campaign or auction, and therefore yields the most revenue (Theorem 4). The effect of independent managed campaigns, on the other hand, is ambiguous and reflects the outcome of a three-way surplus distribution. Holding fixed the price charged

³The autobidding algorithm that allocates budgets can be interpreted as maximizing profit subject to a return on investment constraint. Alternatively, we can decompose the advertising budget into a payment per winning bid for each consumer value. In this case, one can show that the bidding algorithm boosts the bids of the advertisers, but never beyond the value of the match. Thus, the autobidding mechanism satisfies an ex-post participation constraint for every (winning and losing) bid.

to consumers off platform, the managed campaign allows the platform to extract more of the advertisers’ profit relative to the auction. At the same time, when the managed campaign leads advertisers to lower their off platform prices, consumer surplus increases on both channels, potentially lowering the platform’s net revenue (Proposition 8).

1.2 Related Literature

In our digital advertising model, each advertiser has a parallel sales channel available off the platform and faces two values of consumers, *shoppers* on the platform and *loyal customers* off the platform, as in Varian (1980). The design of the auction is therefore subject to competition from a separate and distinct market. Earlier papers referred to mechanism design subject to alternative markets as “partial mechanism design,” or “mechanism design with a competitive fringe,” e.g., Philippon and Skreta (2012) Tirole (2012), Calzolari and Denicolò (2015), and Fuchs and Skrzypacz (2015). In these papers, the platform is limited in its ability to monopolize the market since the sellers have access to an outside option. We focus on digital advertising through auctions rather than competition for the consumer between on and off platform sellers.

Our paper also contributes to the literature on online ad auctions. A recent literature studies learning in repeated auctions (Balseiro and Gur, 2019; Kanoria and Nazerzadeh, 2020; Nedelec et al., 2022), discriminatory effects (Celis et al., 2019; Ali et al., 2019; Nasr and Tschantz, 2020), and collusion (Decarolis et al., 2020, 2022). Our paper is focused instead on comparing the effects of an auction to other allocation mechanisms in the presence of off-platform markets in a static setting and with a fixed information structure.

A key innovation in our model is that the platform actively manages the sellers’ advertising campaigns. Managed campaigns are emerging as the predominant mode of selling advertisements in real-world digital markets: advertisers set a fixed budget, specify high-level objectives for their campaigns, and leave the task of bidding to “autobidders” offered by the platform. Aggarwal et al. (2019), Balseiro et al. (2021), and Deng et al. (2021) offer excellent treatments of this problem in a rapidly growing research area. Several recent papers have focuses on auction design in the presence of autobidders (Liaw et al. (2022); Mehta (2022); Deng et al. (2022)) and return-on-investment constraints (Golrezaei et al. (2021)). Our setting has an additional dimension related to display prices: advertisers submit both bids for the sponsored link and tailored prices to offer the consumers. Li and Lei (2023) investigate mechanisms that allow for these display prices, but we study the impact of activity off the platform in allocations as well as pricing.

The showrooming constraint also relates to a significant literature on digital platforms with competing advertisers or multiple sales channels. Recent contributions on these topics include de Cornière and de Nijs (2016), Bar-Isaac and Shelegia (2020), Miklós-Thal and Shaffer (2021), and Wang and Wright (2020). Different from these papers, the advertisers in our model are concerned about showrooming because selling on the platform can be more profitable thanks to the added value of making data-augmented offers. In parallel work, Bergemann and Bonatti (2022) study on- and off-platform competition with multi-product sellers and associated nonlinear pricing. Relative to our paper, they focus on the implications of managed campaigns for the equilibrium product quality.

2 Model

There are J firms indexed $1, 2, \dots, J$, each selling unique indivisible products, and a single digital platform. Each firm has zero cost of producing its product. There is a unit mass of consumers, each demanding a single product. Willingness to pay for each firm's product is drawn independently across consumers and firms according to a distribution function F with support on $V = [0, 1]$. We assume F admits a log-concave density f on its support ⁴. The vector of consumer values is the consumer's *value*

$$v = (v_1, \dots, v_J) \in [0, 1]^J.$$

The utility for consumer v of purchasing product j at price p_j is

$$U_j(v) = v_j - p_j.$$

Initially, values are observed by the consumers and by the platform, but not by the firms. Because the consumers and the platform share the same information, we are implicitly assuming that the platform has already learned everything about the consumer preferences.

The symmetry in the information is helpful for the welfare comparison but is clearly a stark assumption. The equilibrium implications are robust to a more general formulation in which the platform is endowed with potentially endogenous information, which is intermediate between the complete information of the consumers and the prior information of the advertisers.

⁴This is a technical assumption that ensures that first-order conditions for maximization problems we consider later are well-defined.

2.1 Platform

A measure $\lambda \in [0, 1]$ of consumers uses the platform. The platform presents on-platform consumers with a single “sponsored” result first, followed by organic search results, i.e., a list of non-sponsored products. The platform sells the sponsored position using either a second-price auction or a managed campaign. Under either mechanism, the firm in the sponsored slot can condition its price to the consumer’s value.

Let v denote the full J -dimensional consumer value. An on-platform consumer with value v will see a sponsored offer, which offers some firm j ’s product at some price. In the remaining sections of the paper, we discuss mechanisms for the platform to determine which firm’s offer gets shown to on-platform consumers, and at what price. Note the platform does not ex-ante commit to steer consumers efficiently; that is, value v does not have to see a sponsored offer from j such that $j = \arg \max_i v_i$.

2.2 Firms and Showrooming

In addition to the on-platform prices $p_j(v)$ displayed in the sponsored slot, each firm j sets a fixed posted price \bar{p}_j for its product off the platform. Further, we suppose the firms are subject to a *showrooming* constraint: that is, for all v , $p_j(v) \leq \bar{p}_j$. One interpretation of the showrooming constraint is that on-platform consumers can search for free at any off-platform website or store. Alternatively, the platform may impose most-favored-nation clauses that require sellers to offer their lowest prices on the platform. Note that we use the upper-bar notation here since the showrooming constraint implies that the posted price \bar{p}_j is an upper bound on the amount that any consumer will pay for j ’s good.

2.3 On-platform Consumers

The on-platform consumers observe their willingness to pay v , the “sponsored” offer $p_j(v)$ for the firm j that wins the sponsored slot auction, and the posted prices \bar{p}_k for all firms k . Equivalently, we can interpret the model as allowing for free online search; that is, only a “sponsored” firm can target a price offer to an online consumer, but the online consumer can search and find the posted prices of all firms, including those that did not make the sponsored offer.

2.4 Off-platform Consumers

We assume that the remaining $1 - \lambda$ mass of consumers are loyal, and visit only a single firm’s non-platform store (e.g., physical store, store website). Thus the off-platform consumer population is divided into J segments of size $(1 - \lambda)/J$, where the j th segment shops directly from firm j . Firm j is the only firm in the consideration set of the j th segment of off-platform consumers. The off-platform consumers view the off-platform price of the single firm in their consideration set, and choose to buy if and only if the off-platform price is lower than their willingness to pay.

3 Data-Augmented Bidding

In this section, we characterize the symmetric Bayesian Nash equilibrium of the bidding and pricing game among the advertisers. Each firm j submits a bid function $b_j : V^J \rightarrow \mathbb{R}_+$ and a sponsored price function $p_j : V^J \rightarrow \mathbb{R}_+$, in addition to (simultaneously) posting a price \bar{p}_j . We refer to this as *data-augmented bidding*, because the platform’s proprietary data enables the advertisers to condition bids and sponsored prices on the consumer’s full value vector v .

Let us first discuss some of the economic intuition for how the presence of the platform impacts the prices posted by the firms before presenting the formal analysis. Recall that the off-platform consumers are loyal, and so in the absence of a platform, all firms post the monopoly price for their market segment. Adding the platform and the on-platform consumers has two contrasting effects on the prices posted by the firms. The first effect is an upward pressure due to the increased ability to price discriminate; that is, since the posted price sets an upper bound on the prices that a firm can offer to on-platform consumers, the potential to price discriminate more effectively on-platform pushes firms to raise their posted prices. However, there is an opposite effect, where competition for the on-platform consumers introduces an incentive to lower the posted prices—the ability to undercut its competitors by advertising a lower off-platform price, in order to win more on-platform consumers.

3.1 Bidding Equilibrium

The following result helps characterize the equilibrium strategies of the firms for this setting. Effectively, the proposition shows that *regardless* of the profile of posted prices set by the firms, the bidding equilibrium on the platform results in a *symmetric* assignment, where each on-platform consumer sees a sponsored offer from the firm they like best. This implies

that the sponsored-slot allocation resulting from data-augmented bidding is efficient.

Proposition 1 (Bidding Efficiency)

Fix any vector of posted prices \bar{p} . Consider an on-platform consumer, with value v . If $v_j > v_k$, then in any bidding equilibrium, firm j bids at least as much as firm k for consumer v .

Proof. Suppose $v_j > v_k$. Note that since the platform mechanism is a second-price auction, it is weakly dominant for each firm to bid exactly what the online consumer is worth to that firm. We proceed using casework. As a useful reference, denote by

$$\underline{u} = \max(\max_{i \neq j, k} (v_i - \bar{p}_i), 0),$$

the utility the consumer would get from all firms except j and k . \underline{u} thus is a lower bound on the utility that is conceded to any consumer that does purchase from j or k .

First, consider the cases where $\bar{p}_k \geq \bar{p}_j$. Note that this implies $v_j - \bar{p}_j > v_k - \bar{p}_k$. There are two subcases to consider: either $v_j > \bar{p}_j$ or $v_j \leq \bar{p}_j$. In the first subcase, the highest price that firm j can charge is restricted by showrooming and the nonnegativity constraint, so $b_j(v) = \max(\min(\bar{p}_j, v_j - \underline{u}), 0)$. If firm k were to win the auction, then firm k 's offer must guarantee at least $v_j - \bar{p}_j$ utility to the consumer to dissuade the consumer from going off-platform, and hence the most that firm k can offer is

$$\begin{aligned} b_k(v) &\leq \max(\min(v_k - (v_j - \bar{p}_j), v_k - \underline{u}), 0) \\ &= \max(\min(\bar{p}_j - (v_j - v_k), v_k - \underline{u}), 0) \\ &< \max(\min(\bar{p}_j, v_j - \underline{u}), 0) = b_j(v). \end{aligned}$$

For the second subcase, since $v_j \leq \bar{p}_j$, the consumer is worth v_j to firm j , so $b_j(v) = \max(v_j - \underline{u}, 0)$. Then $v_k < v_j \leq \bar{p}_j < \bar{p}_k$, so the consumer is worth v_k to firm k , and the bids satisfy the following condition

$$b_k(v) = \max(v_k - \underline{u}, 0) \leq \max(v_j - \underline{u}, 0) = b_j(v).$$

Now, consider the cases where $\bar{p}_j > \bar{p}_k$. We have four subcases here.

1. $v_k < \bar{p}_k$ and (a) $v_j < \bar{p}_j$ or (b) $v_j \geq \bar{p}_j$,
2. $v_k \geq \bar{p}_k$ and (a) $v_j \leq v_k + \bar{p}_j - \bar{p}_k$ or (b) $v_j > v_k + \bar{p}_j - \bar{p}_k$.

In subcase (1)(a), $v_j < \bar{p}_j$ and $v_k < \bar{p}_k$, so the highest price j can charge is v_j and the highest price k can charge is v_k . Then $b_k(v) = \max(v_k - \underline{u}, 0)$ and $b_j(v) = \max(v_j - \underline{u}, 0)$, and so

$$b_k(v) = \max(v_k - \underline{u}, 0) \leq \max(v_j - \underline{u}, 0) = b_j(v).$$

In subcase (1)(b), $v_j \geq \bar{p}_j > \bar{p}_k > v_k$, so $v_j - \underline{u} \geq v_k - \underline{u}$ and $\bar{p}_j \geq v_k - \underline{u}$. Hence

$$b_k(v) = \max(v_k - \underline{u}, 0) \leq \max(\min(\bar{p}_j, v_j - \underline{u}), 0) = b_j(v).$$

In subcase (2)(a), $v_k \geq \bar{p}_k$ and $v_j \leq v_k + \bar{p}_j - \bar{p}_k$. Firm j must concede at least $v_k - \bar{p}_k$ utility to the consumer (else the consumer would buy k 's product), and hence the bid

$$\begin{aligned} b_k(v) &= \max(\min(\bar{p}_k, v_k - \underline{u}), 0) \\ &\leq \max(\min(\bar{p}_k + (v_j - v_k), v_j - \underline{u}), 0) \\ &= \max(\min(v_j - (v_k - \bar{p}_k), v_j - \underline{u}), 0) \\ &= b_j(v). \end{aligned}$$

Finally, in the last subcase, note that $v_j - \bar{p}_j \geq v_k - \bar{p}_k$. The bids are

$$b_k(v) = \max(\min(\bar{p}_k, v_k - \underline{u}), 0) \leq \max(\min(\bar{p}_j, v_k - \underline{u}), 0) \leq b_j(v).$$

In all cases, $b_k(v) \leq b_j(v)$. □

To gain some intuition for this result, suppose a consumer arrives, and the consumer's favorite seller is firm 1. Consider a competitor, say firm 2. If firm 1 has set a higher posted price than firm 2, then firm 1 has a larger ability to price discriminate than firm 2, and hence the consumer is intuitively worth more to firm 1, thus allowing it to bid more. However, if firm 1 has a lower posted price than firm 2, then firm 2 must concede rent to the consumer, because even if 2 won the sponsored slot, the consumer could still search and find the posted price for firm 1; hence, this disciplines firm 2's bid, and we show that this actually constrains 2's bid to be lower than 1's.

Proposition 1 is useful because it allows us to separate the bidding stage from the posted prices; that is, the matches (though not the bids) in the bidding game are invariant with respect to the posted prices. As a consequence of this Proposition, the set of online consumers who purchase from firm j is exactly those for whom $j = \arg \max_i v_i$; that is, the consumers with the highest value for firm j 's product.

Since we are looking for symmetric equilibria, we suppose all the other firms post price p' and consider the best response problem of a single firm:

$$\max_p \left\{ \frac{1-\lambda}{J} p(1-F(p)) + \lambda \Omega(p; p') \right\}, \quad (1)$$

where

$$\Omega(p; p') = \int \int^v (\min(v - \max(v' - p', 0), p) - (\min(v' - \max(v - p, 0), p'))_+) dF^{J-1}(v') dF(v).$$

This term denotes the expected profit from on-platform consumers that a firm would expect to make by setting a posted price at p when all other firms set a posted price p' . The term integrates over $v' = \max_{j \neq i} v_j$, which is the highest value the consumer has for any other firm besides i . Since the firm must concede utility $\max(v' - p', 0)$ to the threat of the on-platform consumer going to the competitor, the firm setting price p will bid $\min(v - \max(v' - p', 0), p)$. The highest competitor bids $(\min(v' - \max(v - p, 0), p'))_+$, where $(\cdot)_+$ denotes the nonnegative part. It turns out that with some casework, we can simplify this expression for the on-platform sales further:

Lemma 1 (On-platform Bidding Profit)

The expected on-platform profit satisfy

$$\Omega(p; p') = \int \int^v \min(v - v', p) dF^{J-1}(v') dF(v).$$

Note that v' is only integrated on values less than v . The proof is algebraic and left to the Appendix. The result, however, is quite intuitive. In a standard second-price auction, the expected surplus of a bidder is the expected gap between the bidder value v and the value of the second highest bid v' ; this form shows that with the showrooming constraints and strategic bidding behavior in presence of the off-platform interaction, the firm profit is $v - v'$, capped by the posted price.

To solve for the symmetric equilibria, we take a first-order condition, so we need to compute the derivative of Ω with respect to p . Long but straightforward algebra yields the following expression:

$$\frac{\partial \Omega(p; p')}{\partial p} = \int_p F^{J-1}(v - p) dF(v). \quad (2)$$

Finally, we can write out the first-order condition for profit maximization using (2):

$$\frac{1-\lambda}{J} (1 - F(p) - pf(p)) + \lambda \left(\int_p F^{J-1}(v-p) dF(v) \right) = 0.$$

Rearranging this condition, we summarize the equilibrium characterization as follows.

Theorem 1 (Bidding Equilibrium)

In the unique symmetric equilibrium, the posted prices of the firms satisfy

$$p_B = \frac{1 - F(p_B) + \frac{\lambda J}{1-\lambda} \left(\int_{p_B} F^{J-1}(v-p_B) dF(v) \right)}{f(p_B)}. \quad (3)$$

Firms bid their true value $\max(v_j, p_B)$ for each consumer on-platform. On-platform consumers buy the sponsored offer, and off-platform consumers buy from the firm they are loyal to if and only if the posted price is below their value.

We denote the symmetric equilibrium price for the product off the platform in the presence of the bidding mechanism on the platform by p_B , where we use subscript B as this is the bidding equilibrium.

3.2 Welfare and Comparative Statics

First, we discuss the efficiency implications of the outcome of data-augmented bidding. Proposition 1 implies that the allocation on-platform is socially efficient; since the sponsored offer is always made by the consumer's most preferred firm, each on-platform consumer purchases the product they like best. Off-platform consumers face two sources of inefficiency; first, they might be unaware of the existence of a firm that they would prefer, and second, since the firms only sell to off-platform consumers via posted prices, consumers with value for their firm's product below the posted price will not buy.

To characterize the efficiency implications for the off-platform consumers, we first define the posted price a firm would set if it only had its loyal off-platform population:

$$p_M = \frac{1 - F(p_M)}{f(p_M)}. \quad (4)$$

We term this p_M , as this is analogous to the monopoly price.

Examining the price equations, one can see that since the expression on the right hand side of (3) is a larger function of the price than in (4), the price p_B is larger than p_M . Note

here that higher posted prices entail greater welfare loss off-platform than if the platform did not exist. Since higher prices means both fewer sales, lower consumer surplus, and less efficiency, the presence of the on-platform consumers induces the firms to price out some off-platform consumers in order to gain sales on-platform. Hence, between the two effects discussed at the beginning of the section, it is the incentive to raise posted prices in order to more effectively price discriminate that dominates any competitive effect of the firm interaction on-platform.

Proposition 2 (Posted Prices)

The posted price with data-augmented bidding results in higher posted prices than would occur without the platform, $p_B \geq p_M$. The presence of the platform induces lower consumer surplus, higher posted prices, and lower total welfare off the platform.

In fact, we can generalize the insight to show comparative statics with respect to the share λ of consumers that are on the platform, fixing the total measure of consumers to 1. We will first define several welfare objects of interest, as functions of the posted price p . The expected consumer surplus of an off-platform consumer is:

$$CS_{\text{off}}(p) = \int_p^1 (v - p) dF(v).$$

The expected consumer surplus of an on-platform consumer is:

$$CS_{\text{on}}(p) = \int_p^1 (v - p) dF^J(v).$$

Total consumer surplus is then:

$$CS(p) = (1 - \lambda)CS_{\text{off}}(p) + \lambda CS_{\text{on}}(p).$$

Since F^J describes the distribution of the maximum value a consumer has for any product, the expected welfare of an on-platform consumer is always larger than an off-platform consumer.

The off-platform profit of a firm, per unit measure of loyal consumers, is given by

$$\Pi_{\text{off}}(p) = p(1 - F(p)).$$

The on-platform firm profit per sponsored offer is given by

$$\Pi_{\text{on}}(p) = J\Omega(p; p) = J \int \left[\int^v \min(v - v', p) dF^{J-1}(v') \right] dF(v),$$

by Lemma 1, where the J term comes from the fact that the firm only makes a sponsored offer to a $1/J$ fraction of the on-platform consumers. Note that the total profit of all firms are given by

$$\Pi(p) = (1 - \lambda)\Pi_{\text{off}}(p) + \lambda\Pi_{\text{on}}(p).$$

Moving on to platform revenue, we note that the revenue generated by a sale to a consumer on the platform by firm j is $\min(v_j, p)$. The total platform revenue is given by the expected value of this minus the value conceded to firms, or

$$\begin{aligned} R(p) &= \lambda \left(\int \min(v, p) dF^J(v) - J \int \left[\int^v \min(v - v', p) dF^{J-1}(v') \right] dF(v) \right) \\ &= \lambda J \left(\int \left[\min(v, p) F^{J-1}(v) - \int^v \min(v - v', p) dF^{J-1}(v') \right] dF(v) \right) \\ &= \lambda J \left(\int^p \int^v v' dF^{J-1}(v') dF(v) + \int_p \int_{v-p}^v v' dF^{J-1}(v') dF(v) \right). \end{aligned}$$

Lastly, the total welfare per consumer off-platform is given by

$$W_{\text{off}}(p) = \int_p^1 v dF(v),$$

since only consumers with value larger than p buy. On-platform, the total welfare per consumer is

$$W_{\text{on}} = \int v dF^J(v),$$

since there is allocative efficiency on-platform regardless of the posted prices. The total welfare is

$$W(p) = (1 - \lambda)W_{\text{off}}(p) + \lambda W_{\text{on}}.$$

We then have the following comparative statics in λ , the market share of the platform.

Proposition 3 (Platform Size)

The following comparative statics hold:

1. The posted price with data-augmented bidding p_B is increasing in λ .
2. The expected surplus of on-platform and off-platform consumers is decreasing in λ .
3. The expected off-platform firm profit per consumer Π_{off} is decreasing in λ , and the expected on-platform firm profit per consumer Π_{on} is increasing in λ .
4. Platform revenue is increasing in λ .
5. Off-platform welfare per consumer W_{off} is decreasing in λ .

We also have the following comparative statics with respect to the number of sellers J .

Proposition 4 (Number of Bidders)

If $J > 1/(\ln F(1 - p_M))$, then the following hold:

1. The equilibrium posted price with data-augmented bidding p_B is decreasing in J .
2. Expected consumer surplus both off- and on- platform are increasing in J , and so total consumer surplus increases in J .
3. Welfare per consumer off- and on- platform are both increasing in J , and so total welfare also increases in J .

The proofs are left to the appendix, but we will illustrate many of these comparative statics with a simple example.

Example Consider the setting where the distribution F is uniform on $[0, 1]$. Note that in this setting, since the distribution is uniform, the monopoly price is $p_M = 0.5$. We plot the equilibrium posted prices, total firm profit, and consumer surplus resulting from data-augmented bidding for $J = 3, 5, 7$ in Figure 1. As shown in Proposition 3, for any J , the prices are increasing in λ .

Figure 2a depicts the consumer surplus as a function of λ . We note that total consumer surplus is increasing in λ . Initially the welfare gains from moving consumers from being loyal to shopping over all firms dominates (moving consumers from welfare level CS_{off} to CS_{on}) but as the platform becomes too large, the increasing ability to price discriminate

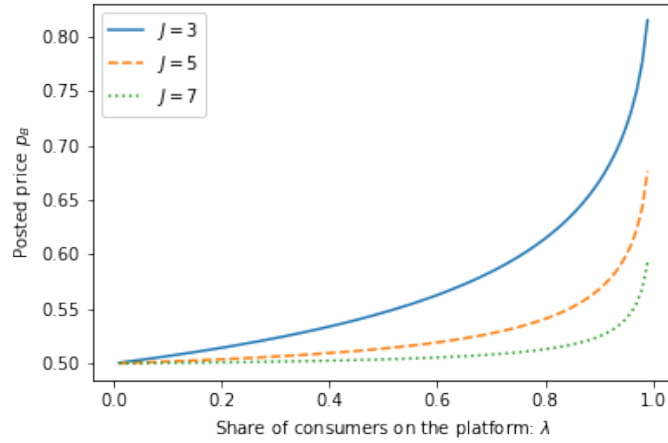
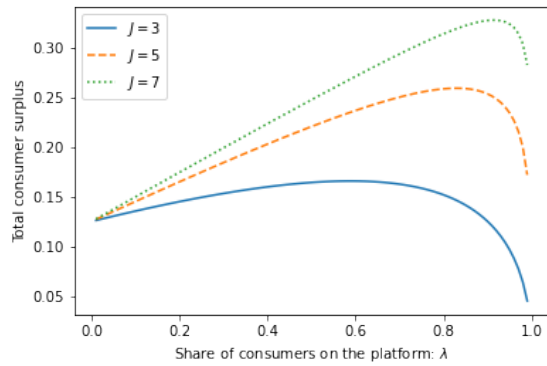
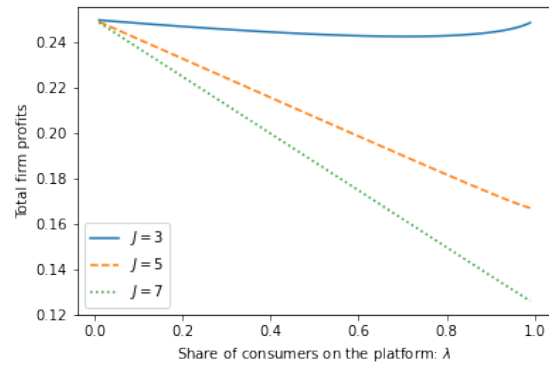


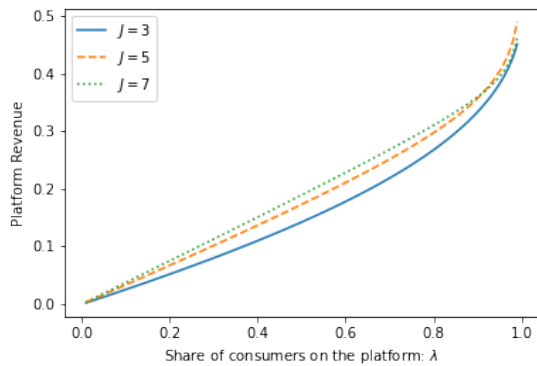
FIGURE 1: Posted prices as a function of λ . Results are plotted for $J = 3, 5, 7$.



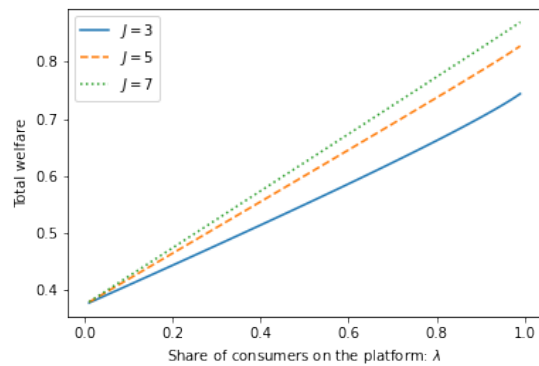
(A) Total Consumer Surplus



(B) Total Firm profit



(C) Platform Revenue



(D) Total Welfare

FIGURE 2: Consumer surplus, firm profit, platform revenue, and welfare with data-augmented bidding as a function of the share of consumers on the platform, λ . Results are plotted for $J = 3, 5, 7$.

on the platform dominates and consumers lose welfare. Hence, total consumer surplus is nonmonotone in λ .

Figure 2b depicts firm profit as a function of λ . Here, firm profit for $J = 3$ are nonmonotone. As mentioned in Proposition 3, the profit per consumer off-platform are decreasing in λ and the profit per consumer on-platform are increasing in λ , and so the overall effect on total profit depends on which force dominates.

Figure 2c depicts the platform revenues as a function of λ . As expected, platform revenues are increasing in λ . However, the interesting feature of this example in platform revenue is that for very large platforms, λ close to 1, the platform revenue can be nonmonotone in J , the number of firms. The two contrasting forces here are that with more firms, the expected value of second-highest bids will be higher, which would suggest that platform revenue should be increasing in J . However, with more firms, as shown in Figure 1, posted prices can be pushed down, thus reducing the price-discriminating ability of the firms on-platform and pushing down the platform revenues.

Figure 2d shows that total welfare is increasing in both λ and J , as would be expected.

3.3 Participation Fees

In the bidding model discussed so far, the platform received revenues only from the bids of the advertiser. We now ask whether tools from optimal auction design such as participation fee of reserve price may increase the revenue of the platform.⁵ In particular, as advertisers have no prior information about the consumers ex ante, we investigate how a participation fee for the second-price auction would affect the division of surplus between platform and advertisers. Thus, we consider the following game:

1. The platform sets a participation fee T .
2. The firms choose whether to pay the participation fee and set their posted prices.
3. If all firms accept, the platform runs a second-price auction for the on-platform consumers. If some firm rejects, the platform can assign the sponsored offers however it would like.

The platform maximizes revenue, and we will assume a firm that is indifferent about accepting chooses to accept. As such, the platform extracts all the producer surplus, up to an outside option the firm could obtain by refusing to participate.

⁵The importance of such tools in online ad auctions has been widely documented, e.g., by Ostrovsky and Schwarz (2016) for the case of reserve prices.

Proposition 5 (Equilibrium with Participation Fees)

In equilibrium all firms join, the off-platform posted prices of all firms are given by (3). Firms bid their true value $\max(v_j, p_B)$. Firm profit are held to their outside option:

$$\Pi_O = \max_p \left\{ \frac{1-\lambda}{J} p(1-F(p)) + \lambda \int_p F^{J-1}(v-p) dF(v) \right\}. \quad (5)$$

The transfer charged by the platform holds firms to this outside option.

Intuitively, the pricing and bidding behavior follow as in Theorem 1 due to subgame perfection. The transfer charged is as large as possible to make firms indifferent between accepting and rejecting. The proof is left to the appendix.

To gain a bit of intuition for the outside option profit expression, the first part of the expression is the profit from selling to the loyal consumers; the second integral expression denotes the profit the firm makes due to the ability of on-platform consumers to search; upon rejecting the platform's service, the firm could still be found by consumers with a sufficiently high value for its product, provided the consumer's value v satisfies $v - p > v'$, where v' is the consumer's value for the best competitor.

4 Managed Advertising Campaigns

In a managed advertising campaign, the platform determines which firm wins the sponsored slot, and makes an offer to that consumer on behalf of that firm. The platform collects an ex-ante fee for this service from each participating firm. Thus, it is the platform rather than the advertising firms that selects the bidding functions and the product prices. The key difference is therefore that the firms relinquish agency over the on-platform allocation process to the platform, though they still collect the revenue from on-platform sales. The firms giving up this agency is why we refer to this as a *managed* campaign. However, the firms still make decisions on participation and on posted prices. In the first subsection, we examine a form of *independent* managed campaigns where the platform cannot condition on-platform sponsored pricing based on the posted prices of the firms, and in the second subsection we consider a *sophisticated* managed campaign where the platform does condition the on-platform sponsored pricing on the posted prices of firms.

We will be explicit about the extensive form of the game in both the independent and the sophisticated managed campaign subsection. In each setting, we consider subgame perfect equilibrium.

4.1 Independent Managed Campaigns

We first describe a model where the platform offers automated pricing on-platform, and the firms pay a participation fee and set posted prices. Let $a_j \in \{0, 1\}$ denote firm j 's acceptance decision of the mechanism offered by the platform. The game proceeds as follows:

1. The platform proposes to all firms a mechanism (s, p, T) , where $s : V^J \times \{0, 1\}^J \rightarrow J$ is a *steering policy*, $p : V \times \{0, 1\}^J \rightarrow \mathbb{R}_+$ is a *pricing policy*, and $T \in \mathbb{R}_+^J$ is a profile of lump-sum transfers.
2. The firms simultaneously decide whether to accept ($a_j = 1$) or reject ($a_j = 0$) the platform's offer and what off-platform price \bar{p}_j to post.
3. If a firm accepts the platform's offer, that firm pays the transfer T_j ; if a firm rejects, the firm pays no transfer. Given the vector of participation decisions $a = (a_i)_{i=1,2,\dots,J}$, the platform then makes sponsored offers to the on-platform consumers according to the steering policy s with the corresponding price determined p . Specifically, consumer $v \in V^J$ sees the offer of firm $j = s(v, a)$ at price $p(v_j, a)$.

Intuitively, a steering policy maps consumer value and a profile of acceptances to a choice of firm to steer the consumer towards. The pricing policy maps the consumer value for the steered firm's product and the acceptance profile into a price. The dependence on the acceptance profile allows the platform to react to the firms' participation decisions. In particular, we use $\vec{1}$ to denote the vector $(1, 1, \dots, 1)$ of all firms participating.

In this mechanism, the platform collects an ex-ante fee for its on-platform consumers and its data that allows for price discrimination. Thus, it bundles both access and price discriminating ability and charges the fee for the bundle. Note that the bundling of these two services implies that if firms set posted prices off the equilibrium path in the third stage, the platform still makes price discriminating offers and some consumers could potentially be poached by other firms via the search ability of online consumers. That is, the steering policy guarantees the firms the opportunity to price discriminate on the segment of on-platform consumers, but the firm could still lose consumers to search. However, in the equilibrium characterization we show that this does not happen on-path.

An important part to emphasize is that the price policy can only condition on the value the consumer has for the steered firm and the participation decisions. In particular, this forces the platform to price *independently* of the posted price decisions and the consumer's value for alternatives, which curtails the ability of the platform to interfere with competition.

As a note to break ties, if the platform can propose two revenue-equivalent mechanisms but one mechanism results in more on-platform consumers purchasing their sponsored offers, the platform prefers the mechanism where more on-platform consumers purchase their sponsored offers.

Proposition 6 (Efficient Platform Steering)

An optimal strategy for the platform is to steer the consumer efficiently among the participating firms:

$$s(v, a) = \arg \max_j v_j \text{ s.t. } a_j = 1.$$

Note that firms are not perfectly excludable from the platform; that is, if a firm rejects, on-platform consumers can still search to find the rejecting firm. Since the participation decision of the firms depends on whether the transfer is worth the change in sales dictated by the steering policy, an optimal strategy for the platform in the case of a firm rejection is to offer products for free. More precisely, we have the following result:

Lemma 2 (Outside Option)

An optimal strategy for the platform sets $p(\cdot, a) = 0$ if $a \neq \vec{1}$.

The proof is left to the appendix, but the key idea is that in order to punish non-participation, the platform has to ensure that if any firm chooses not to participate, their profit are held to the outside option, with profit characterized by (5).

Now consider the pricing policy of the platform. Because it is optimal for the platform to steer efficiently, and firms are ex-ante symmetric, we look for symmetric equilibria in the pricing subgame on the equilibrium path where all firms join the platform. First, suppose the platform offered only first-degree price discrimination, and consider the best response problem of a single firm. Suppose the other firms have set off-platform prices p' , and consider the best-response problem of firm j . As we are interested in symmetric equilibria, we take $p \rightarrow p'$. We obtain the first order condition

$$0 = \frac{1 - \lambda}{J} (1 - F(p) - pf(p)) + \lambda \left(\int_p (F^{J-1}(v) - p dF^{J-1}(v)) dF(v) \right). \quad (6)$$

Intuitively, the term multiplying λ in the first order-condition (6) can be decomposed into two effects; the first term, $\int_p F^{J-1}(v)dF(v)$ denotes the marginal increase in price-discriminating profit from raising the offline price (as the firm j earns an additional profit on the measure of consumers whose value for good j is above p , and values their good more than the other $J - 1$ firms. The second term denotes the loss due to consumers being poached: by

raising the offline prices, a marginal fraction $\int_p dF^{J-1}(v)dF(v)$ of consumers that the firm was originally selling to (and making profit p) are lost to other firms, and so the profit loss there is $-p \int_p dF^{J-1}(v)dF(v)$.

The pricing condition (6) will determine a candidate posted price equilibrium; however, whether this is indeed an equilibrium depends on whether the price that satisfies this implicit equation is higher or lower than the monopoly price. That is, since the platform offers policies such that on-platform consumers purchase online, the platform will find it optimal to offer pricing policies of a particular form:

Lemma 3 (Platform Pricing Policy)

It is weakly optimal for the platform to offer first degree price discrimination up to some cap; that is, $p(v_j, \vec{1}) = \min(v_j, \hat{p})$, where \hat{p} is the cap.

Again, the formal proof is left to the appendix; the key idea is that first-degree price discrimination up to a cap minimizes the maximum price offered by the platform conditional on each firm earning some fixed amount of sales; that is, for any level of firm sales on-platform, there exists a price cap that generates the same level of sales with a weakly lower maximum price charged to any consumer.

The platform introducing a price cap implies that the best-response profit of the firms kink at \hat{p} . If the price satisfying (6) above is above the monopoly price p_M , then the platform can offer pricing policies capped at the price satisfying (6) and firms have no incentive to deviate by raising their off-platform prices; that is, \hat{p} would satisfy the first order condition from (6) since the best-response problem of the firm kinks downward.

However, if the price implied by (6) is lower than the monopoly price, then the platform sets the price at the solution to (6), the firms would respond by setting posted prices to the monopoly price to retain off-platform profit. In this case, the platform chooses a price cap at \hat{p} that is as large as possible such that firms still select posted prices at p_M . That is, the deviating profit of a single firm from setting some posted price to try to poach consumers on-platform is given by

$$\Pi_U(\hat{p}) = \max_{p \leq \hat{p}} \left[\frac{1-\lambda}{J} p(1-F(p)) + \lambda \left(\int^p v F^{J-1}(v) dF(v) + \int_p p F^{J-1}(\min(v + \hat{p} - p, 1)) dF(v) \right) \right].$$

We subscript this profit expression with a U to indicate that this is the largest profit that the firm could get by undercutting other firms. Intuitively, it maximizes over undercutting

prices less than p_M assuming that all other firms see the on-platform prices dictated by the platform's pricing policy capping prices at \hat{p} . The first term is the sales from off-platform consumers. The first integral term is the profit from sponsored offer sales, and the second integral captures the profit from on-platform consumers that the firm would poach away from other firms.

In order for the firms to prefer setting the monopoly price as the posted price, the value of Π_U then must be less than the individual firm profit from following the equilibrium. We can write out the profit a firm receives from setting p_M when the price cap \hat{p} is below p_M as

$$\Pi_M(\hat{p}) = \frac{1-\lambda}{J} p_M (1 - F(p_M)) + \lambda \left(\int \min(v, \hat{p}) F^{J-1}(v) dF(v) \right).$$

Intuitively, Π_M is the profit a firm receives from setting the monopoly price as the posted price when the platform's pricing policy caps prices at \hat{p} .

Let p_C be the candidate posted price equilibrium, the price satisfying the first order condition (6); that is,

$$p_C = \frac{1 - F(p_C) + \frac{\lambda J}{1-\lambda} \left(\int_{p_C} (F^{J-1}(v) - p_C dF^{J-1}(v)) dF(v) \right)}{f(p_C)}. \quad (7)$$

As argued before, if $p_C < p_M$, the platform extracts the most revenue when offering pricing policies capped at p^* defined by

$$p^* = \max \{p \in [p_C, p_M] \mid \Pi_U(p^*) \leq \Pi_M(p^*)\}. \quad (8)$$

Thus, p^* is the largest price cap such that firms do not find it beneficial to deviate downward to undercut prices when other firms are pricing at the monopoly price p_M . That is, the price cap in the pricing policy offered by the firms has to be low enough to dissuade undercutting, and the platform offers the largest such cap. In the proof of the following theorem, we show that p^* exists.

Theorem 2 (Independent Managed Campaign Equilibrium)

The symmetric managed campaign equilibrium has the platform offer efficient steering. The nature of the equilibrium depends on p_C relative to p_M .

1. If $p_C \geq p_M$, the platform's pricing policy to firm j is $p_j(v) = \min(v_j, p_C)$; that is, price discriminating up to p_C . Firms set posted prices at p_C .
2. If $p_C < p_M$, the platform's pricing policy to firm j is $p_j(v) = \min(v_j, p^*)$; that is, price discriminating up to p^* . Firms set posted prices at p_M .

We relegate the formal proof to the appendix. It is important to note that the posted prices set by firms satisfies:

$$p_I = \max(p_C, p_M). \tag{9}$$

We use subscript I here since p_I denotes the off-platform posted price of the firms for the independent managed campaign; it is equal to the candidate p_C identified by the first-order condition (6) if it is larger than the monopoly price, but is the monopoly price otherwise.

In Proposition 2, we showed that in data-augmented bidding, the posted price is larger than the monopoly price. This implies that the incentive to raise posted prices introduced by the potential to price discriminate dominates the downward force on posted prices introduced by competition for on-platform consumers. However, we present two examples that show that this is not necessarily the case when the platform is running a managed campaign. We first present an example of an environment where the price discrimination effect still dominates and so $p_C > p_M$, and secondly present another environment where the competitive effect dominates, and so the platform actually does not induce the firms to raise prices on off-platform consumers.

Example ($p_C > p_M$) We first provide an example of an environment where the price discrimination effect dominates. Take a uniform distribution of values ($F(x) = x$), and suppose there is an equal share of on-platform and off-platform consumers ($\lambda = 1/2$), and consider two firms. From the pricing equation (7), we get

$$p_C = 1 - p_C + 2 \int_{p_C}^1 (v - p_C) dv,$$

$$p_C \approx 0.59 > 0.5 = p_M.$$

Thus, in this case, $p_C > p_M$, and in the presence of the platform, the two firms raise their posted prices as the incentive to price discriminate dominates.

Example ($p_C < p_M$) Now we provide an example where the competitive effect dominates. Consider almost the exact same environment as the previous example (uniform distribution of values, equal share of consumers on- and off-platform) but now, we introduce a third firm. From the pricing equation (7), we get

$$p_C = 1 - p_C + 3 \int_{p_C} (v^2 - p_C(2v)) dv,$$

$$p_C \approx 0.43 < 0.5 = p_M.$$

Here, by adding one firm to the previous example, the competitive effect becomes stronger, and in the managed campaign, on-platform consumers actually see prices capped below the monopoly price p_M . That is, the platform must mitigate competition on-platform by capping on-platform prices below p_M to dissuade firms from undercutting each other and moving to pricing at p_C . We can numerically compute the cap for this example; the platform caps online prices at

$$p^* \approx 0.4648 \in [p_C, p_M).$$

In fact, the insight regarding competition generalizes; that is, with enough firms and a condition on the distribution, the competitive effect on the platform will mitigate the firm's market power off-platform.

Proposition 7 (Price Comparison)

Assume there exists $B > 0$ such that $F(v)/f(v) < B$ for all v . Then for all sufficiently high J , we have $p_C < p_M$.

4.2 Sophisticated Managed Campaign

In the independent managed campaign model, the platform offered the firms the pricing policy without being able to condition on the off-platform prices charged by the firms. However, the platform could take a more active role in softening price competition. For example, it could offer a “best value guarantee” to each firm on a segment of on-platform consumers, which ensures that the price offered is acceptable to the consumer given the vector of posted prices. More generally, we now allow the platform to condition its steering and pricing policies on the vector of posted prices $\bar{p} \in \mathbb{R}_+^J$ set by firms as well as on the consumer's value

$v \in V^J$ and all acceptance decisions $a \in \{0, 1\}^J$. The game has the following extensive form:

1. The platform proposes to all firms a mechanism (s, p, T) , where $s : V^J \times \{0, 1\}^J \times \mathbb{R}_+^J \rightarrow J$ is a *steering policy*, $p : V^J \times \{0, 1\}^J \times \mathbb{R}_+^J \rightarrow \mathbb{R}_+$ is a *pricing policy*, and $T \in \mathbb{R}_+^J$ is a profile of lump-sum transfers.
2. The firms simultaneously decide whether to accept ($a_j = 1$) or reject ($a_j = 0$) the platform's offer and what off-platform price \bar{p}_j to post.
3. If a firm accepts the offer, that firm pays the transfer T , and its product will be offered to a subset of on-platform consumers according to policies s and p .

Here, the pricing policy conditions on the posted prices set by the firms, an important distinction from the independent managed campaign. Specifically, the pricing policy now is a function $V^J \times \{0, 1\}^J \times \mathbb{R}_+^J \rightarrow \mathbb{R}_+$, rather than $V \times \{0, 1\}^J \rightarrow \mathbb{R}_+$; in other words, the platform can now condition its pricing policy on the posted prices set by the firms and the full value vector of the consumer. We first focus on a specific instance of a sophisticated managed campaign, and then show that this specific pricing policy is revenue-optimal for the platform.

Formally, define *best-value pricing* as the pricing policy dictated by:

$$p(v, \vec{1}, \vec{p}) = \min_{k \neq j} (v_j, \bar{p}_j, v_j - v_k + \bar{p}_k) \quad (10)$$

where $j = s(v, \vec{1})$ is the firm the platform steers the consumer towards. Note that the arguments in Proposition 6 still hold in this setting, and so the platform steers efficiently.

Intuitively, best-value pricing ensures that there will never be poaching even off the equilibrium path, or equivalently that the sponsored offer always guarantees the best value to the consumer. In this sense, the best-value pricing guarantee is stronger than a most-favored nation clause that ensures each seller offers their good at a lower price on-platform than off-platform. In addition to doing so, the guarantee in (10) makes sure no competing seller offer a lower price than the sponsored seller.

We then obtain the following equilibrium characterization, where we subscript the off-platform price by V to denote that this results from (best-) value pricing.

Theorem 3 (Sophisticated Managed Campaign Equilibrium)

The symmetric managed campaign equilibrium with best-value pricing has the platform offer efficient steering and the posted prices are characterized by the following implicit equation:

$$p_V = \frac{1 - F(p_V) + \frac{\lambda J}{1-\lambda} \left(\int_{p_V} F^{J-1}(v) dF(v) \right)}{f(p_V)}. \quad (11)$$

The proof is algebraic and involves writing out the profit expressions of the firms and deriving the implicit price characterization in (11) from the first order condition, so it is left to the appendix.

As it turns out, best-value pricing is revenue-optimal for the platform. That is, best-value pricing attains the maximum revenue a platform can achieve in the sophisticated managed campaign setting.

Theorem 4 (Optimal Sophisticated Managed Campaign)

The best-value pricing managed campaign is platform revenue-maximizing among all sophisticated managed campaigns.

Proof. To show this, we consider the problem of a vertically integrated platform that jointly maximizes profit of firms and the platform. The vertically integrated platform can jointly coordinate on-platform and off-platform pricing, but still faces the showrooming constraint due to consumer search capabilities. The vertically integrated firm's problem is then to maximize

$$\max_p \left\{ (1 - \lambda)p(1 - F(p)) + \lambda \int \min(v, p) dF^J(v) \right\}.$$

The first order condition of the planner problem is

$$(1 - \lambda)(1 - F(p) - pf(p)) + \lambda \int_p dF^J(v) = 0.$$

Expanding dF^J , and dividing through by J , we get

$$\frac{1 - \lambda}{J}(1 - F(p) - pf(p)) + \lambda \int_p F^{J-1}(v) dF(v) = 0.$$

But by definition, p_S exactly satisfies this first order condition, and by the characterization in Theorem 6, p_S are exactly the off-platform prices in the sophisticated managed campaign. Thus, this implies that the sophisticated managed campaign necessarily maximizes the joint surplus of the platform and firms.

Now, note that the firms are guaranteed their outside option value (defined in (5)) since in any managed campaign, the firms could refuse to participate. Additionally, note that in the sophisticated managed campaign described, the firms make exactly their outside option, since the transfer the platform charges to each firm makes them exactly indifferent between joining the platform and not. Since the sophisticated campaign maximizes the joint surplus of platform and firm, and concedes the smallest possible surplus to the firms, it follows that the platform earns the most revenue in the sophisticated managed campaign over any managed campaign. \square

In fact, in the proof, we actually showed that the joint surplus obtained by the firms and the platform is maximized for best-value pricing; that is,

Corollary 1 (Producer Surplus)

Producer surplus (sum of firm profit and platform revenue) is maximized for best-value pricing, and equals the profit of a vertically integrated platform that owns the firms.

5 Comparing Advertising Mechanisms

We now compare the equilibrium posted prices and the welfare implications under these two distinct mechanisms, the data-augmented second price auction and the managed campaign mechanism. We start with the comparison of the prices off the platform.

5.1 Posted Prices

Recall the pricing equations (3) and (9), which characterize the offline prices of the firms under bidding and the independent managed campaign.

Theorem 5 (Equilibrium Prices and Surplus Comparison)

Suppose that F^{J-1} is convex. Then

$$p_B \geq p_I.$$

Total social surplus and total consumer surplus are decreasing in p and:

$$CS(p_B) \leq CS(p_I), \quad W(p_B) \leq W(p_I).$$

Further, if F^{J-1} is concave, all the inequalities are reversed.

Proof. The derivative of profit with respect to the posted price in the bidding model is:

$$\frac{1-\lambda}{J}(1-F(p)-pf(p)) + \lambda \left(\int_p F^{J-1}(v-p) dF(v) \right).$$

The derivative of profit with respect to the posted price in the managed campaign model is:

$$\frac{1-\lambda}{J}(1-F(p)-pf(p)) + \lambda \left(\int_p (F^{J-1}(v)-p) dF^{J-1}(v) dF(v) \right).$$

Under the assumption that F^{J-1} is convex, then we have that

$$F^{J-1}(v-p) \geq F^{J-1}(v) - p dF^{J-1}(v).$$

since the right-hand side is a first-order expansion of F^{J-1} around v . Thus, the derivative of profit with respect to posted price is weakly larger in the bidding model, which implies that $p_B \geq p_C$. Since $p_B \geq p_M$ by Proposition 2, $p_B \geq p_I$. As total welfare and total consumer surplus are both decreasing in p , the welfare comparative statics follow.

Note that if F^{J-1} is concave, then

$$0 \leq F^{J-1}(v-p) \leq F^{J-1}(v) - p dF^{J-1}(v),$$

since the right-hand side is a first-order expansion of F^{J-1} around v . As the derivative of profit with respect to posted price is weakly smaller in the bidding model, $p_M \leq p_B \leq p_C$, and the welfare comparative statics hold in the reverse inequality direction from the convex case. \square

In words, posted prices are higher in the bidding equilibrium than the managed campaign equilibrium. Since total welfare and total consumer surplus are both decreasing, total welfare and consumer surplus are both higher under the managed campaign.

To interpret the condition that F^{J-1} is convex, note that F^{J-1} represents the cumulative distribution function of the maximum of $J-1$ values drawn from F . For large enough J , this cumulative distribution function is convex under relatively weak conditions. Indeed, if the density f is such that f'/f is bounded below, then there always exists a J large enough such that F^{J-1} is convex.

Recall that the introduction of the platform introduces two contrasting effects on the incentives of firms setting prices. The first is that the ability to price discriminate on-platform creates an incentive to raise posted prices, since the posted prices limit the price

discriminating ability of the firm. The second is the introduced competitive effect; since on-platform consumers can search for all the firms, the inter-firm competition for consumers pushes down posted prices.

Proposition 2 showed that in data-augmented bidding, the first effect dominates the second, and firms always raise their posted prices above the standalone price. Theorem 5 shows that allowing the platform to run an independent managed campaign actually creates a more competitive environment relative to data-augmented bidding; since firms cannot control their pricing anymore, the threat of poaching is larger, and the competition for on-platform consumers dominates.

Now, recall that in the sophisticated managed campaign discussed in Section 4.2, the platform commits to guaranteeing that its pricing policy ensures that poaching cannot occur; that is, the modified pricing policy of the platform here entirely removes any ability for firms to poach consumers on-platform, so the dominant force on posted prices is the incentive to raise posted prices to discriminate better on-platform.

Theorem 6 (Posted Price Comparison)

The posted prices in the managed campaign with best-value guarantee are higher than both the posted prices in bidding and the independent managed campaign model

$$p_V \geq p_I,$$

$$p_V \geq p_B \geq p_M.$$

Total consumer surplus and total welfare are lowest in this managed campaign variant than under both the bidding equilibrium and the independent managed campaign model.

Proof. Consider the derivative of the best-response profit maximization problem with respect to the posted price for each of the three models. In the bidding model is, we have

$$\frac{1-\lambda}{J} (1 - F(p) - pf(p)) + \lambda \left(\int_p F^{J-1}(v - p) dF(v). \right)$$

In the independent managed campaign model, the derivative of profit maximization characterizing p_C is

$$\frac{1-\lambda}{J} (1 - F(p) - pf(p)) + \lambda \left(\int_p (F^{J-1}(v) - p dF^{J-1}(v)) dF(v) \right),$$

and in the sophisticated campaign, we have

$$\frac{1-\lambda}{J} (1 - F(p) - pf(p)) + \lambda \left(\int_p F^{J-1}(v) dF(v) \right).$$

Note that this third expression is larger than the first two, since $F^{J-1}(v) \geq F^{J-1}(v) - p dF^{J-1}(v)$ and $F^{J-1}(v) \geq F^{J-1}(v - p)$. Hence, we must have $p_V \geq p_C, p_B$. Note that this also implies $p_S \geq p_B \geq p_M$ by Proposition 2; hence it follows then that $p_S \geq p_I$ since $p_S \geq p_C, p_M$. Since welfare and total consumer surplus are both decreasing in posted price, the welfare comparative statics follow. \square

Theorem 6 shows that the platform offering a best-value pricing policy eliminates the threat of poaching and weakens competition between firms; this reduced competition thus results in higher posted prices than both in bidding and in the original managed campaign.

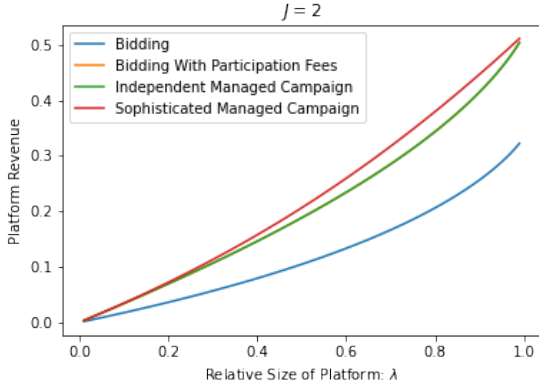
5.2 Platform Revenue

In both managed campaigns and data-augmented bidding, the on-platform allocation is efficient and so the total surplus on-platform is identical. Further, the on-platform consumer surplus decreases with higher posted prices in any mechanism. Theorem 5 states that if F^{J-1} is convex, on-platform consumer surplus is higher in the managed campaign than in data-augmented bidding. As a result, the joint profit of the platform and firms increases with higher posted prices. The platform's ability to extract surplus decreases with lower posted prices, which would decrease platform revenue.

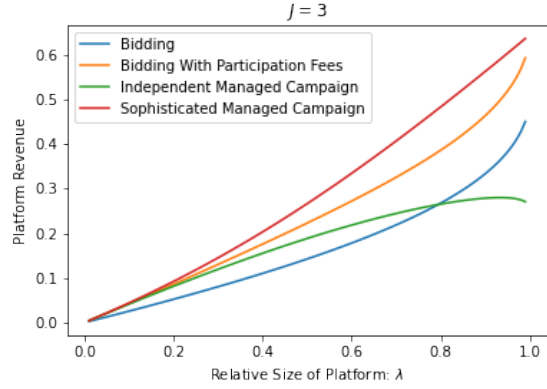
A countervailing force is that the platform sets lump-sum transfers in the managed campaign, so it no longer has to give rents to bidders. Instead, it holds firms to their outside options, which consist of not using sponsored links and responding to competitors' posted and advertised prices. The platform's best response is to ensure that a non-participating firm makes as few sales on-platform as possible.

Indeed, the tradeoff between these two forces determines whether the platform would generate more revenue by letting the firms bid versus running independent managed campaigns themselves. In Figure 3, we plot the revenue generated by the platform in the bidding model and the independent managed campaign as functions of λ when consumer values are drawn from a uniform distribution. Figure 3a shows the revenue when there are $J = 2$ firms, and Figure 3b plots the revenue for $J = 3$ firms.

Figure 3a shows the platform revenue with 2 firms. With $J = 2$ and a uniform distribution of values, we in fact have that F^{J-1} is linear, and so the posted prices resulting from bidding



(A) Platform revenue as a function of λ , $J = 2$



(B) Platform revenue as a function of λ , $J = 3$

FIGURE 3: Platform revenue with consumer values uniformly distributed on $[0, 1]$. In the first figure, the platform revenue from bidding with participation fees and from the independent managed campaign coincide.

and independent managed campaigns are equal. This implies that the first force (lower on-platform surplus extraction due to lower posted prices) does not appear in this case. Therefore, the platform revenues are higher with independent managed campaigns than with data-augmented bidding.

From the figures, one can see that between the normal bidding equilibrium and the independent managed campaign, it can be ambiguous whether the platform prefers the bidding or independent managed campaign; Figure 3a demonstrates a scenario where the independent managed campaign yields more revenue, and for some parameter regimes in Figure 3b, the bidding model yields more revenue. However, if we allow the platform to charge participation fees, it is clear the platform earns more revenue than in the standard bidding model without a participation fee. It is also true that in a bidding model with participation fees, the platform actually earns more than it would by running an independent managed campaign:

Proposition 8 (Revenue Comparison)

If $p_B \geq p_I$, platform revenue in a bidding model with participation fees is weakly higher than in the independent managed campaign. Otherwise, the platform earns less in the bidding model with participation fees relative to the independent managed campaign.

Proof. Note that in both models, the firms are held to their outside options. Hence, whether the platform earns more depends exactly on the producer surplus extracted. By Theorem 4, the off-platform price p_V induced by the sophisticated managed campaign maximizes producer surplus. By Theorem 6, $p_V \geq p_B, p_I$. Since producer surplus is concave in the

off-platform price, p_V maximizes producer surplus, and $p_V \geq p_B, p_I$, the producer surplus is larger in the bidding model if $p_B \geq p_I$ and larger in the independent managed campaign if $p_I \geq p_B$. \square

Finally, as one can see in Figure 3, it is clear that the sophisticated managed campaign results in more platform revenue than in the independent managed campaign and bidding. Intuitively, the platform deters competition through the best-value pricing, resulting higher prices and hence more on-platform surplus extraction by the platform. In fact, since there exist sophisticated mechanisms which implement both the bidding equilibrium and the independent managed campaign, a consequence of Theorem 4 is the following:

Corollary 2 (Platform Revenue Comparison)

Platform revenue in the sophisticated managed campaign is higher than in both the bidding equilibrium and the independent managed campaign.

6 Conclusion

Many digital platforms such as Google, Meta, Amazon, and TikTok generate revenue through advertising by placing ads or sponsored slots on their own and partner websites. These platforms use a bidding and auction mechanism to determine advertisers' willingness to pay and a ranking and recommendation mechanism to select the most suitable ad to display to the viewer. The platform's knowledge about the match value between consumers and products is critical to the success of both mechanisms. This knowledge helps generate the most competitive bids from advertisers in the auction and supports more clicks and other engagement in the ranking mechanism. We proposed an integrated model that considers how auction and data jointly determine the match formation on digital platforms. We also highlighted the value of information and data for the platform in the joint deployment of these services on both sides of the market.

A Appendix

Proof of Lemma 1

First consider the regime $p < p'$. Since the firm only wins the consumers for which $v > v'$, it is always then the case that $v - p > v' - p'$, so the firm never has to concede rents to the threat of the consumer buying from the second-best firm. There are three distinct regions to consider here: if $v < p$, the firm earns v and pays v' . If $v \geq p$, then the firm earns p , but how much the firm pays depends on the second highest bid, and so if $v' < v - p$ the firm pays 0, else the firm pays $v' - (v - p)$. The Ω term in this region is thus given by:

$$\begin{aligned}
 \Omega(p; p') &= \int^p \left(\int^v (v - v') dF^{J-1}(v') \right) dF(v) \\
 &\quad + \int_p^v \left(\int^{v-p} p dF^{J-1}(v') + \int_{v-p}^v (p - (v' - (v - p))) dF^{J-1}(v') \right) dF(v) \\
 &= \int^p \int^v (v - v') dF^{J-1}(v') dF(v) \\
 &\quad + \int_p^v \left(\int^{v-p} p dF^{J-1}(v') + \int_{v-p}^v (v - v') dF^{J-1}(v') \right) dF(v) \\
 &= \int \int^v \min(v - v', p) dF^{J-1}(v') dF(v).
 \end{aligned}$$

Now, suppose $p \geq p'$. We again proceed with casework. If $v < p'$, then no constraints bind and the firm earns v and pays the bid v' . If $v \in [p', p]$ and $v' < p'$, the firm once again earns v and pays v' . If $v \in [p', p]$ and $v' \in (p', v]$, then the firm earns $v - (v' - p')$ and pays p' . If $v > p$, then there are 3 subcases for v' . If $v' < v - p$, the firm earns p and pays 0. If $v' \in [v - p, p' + v - p]$, the firm earns p and pays $v' - (v - p)$. If $v' \geq p' + v - p$, then the

firm earns $v - (v' - p')$ and pays p' .

$$\begin{aligned}
\Omega(p; p') &= \int^{p'} \left(\int^v (v - v') dF^{J-1}(v') \right) dF(v) \\
&+ \int_p^p \left(\int^{p'} (v - v') dF^{J-1}(v') + \int_{p'}^v (v - (v' - p') - p') dF^{J-1}(v') \right) dF(v) \\
&+ \int_p \left(\int^{v-p} p dF^{J-1}(v') + \int_{v-p}^{p'+(v-p)} (p - (v' - (v - p))) dF^{J-1}(v') \right) dF(v) \\
&+ \int_p \left(\int_{p'+(v-p)}^v (v - (v' - p') - p') dF^{J-1}(v') \right) dF(v) \\
&= \int^{p'} \left(\int^v (v - v') dF^{J-1}(v') \right) dF(v) \\
&+ \int_p^p \left(\int^{p'} (v - v') dF^{J-1}(v') + \int_{p'}^v (v - v') dF^{J-1}(v') \right) dF(v) \\
&+ \int_p \left(\int^{v-p} p dF^{J-1}(v') + \int_{v-p}^v (v - v') dF^{J-1}(v') \right) dF(v) \\
&= \int \int^v \min(v - v', p) dF^{J-1}(v') dF(v).
\end{aligned}$$

Finally, to make sure the first-order condition is valid, we take the second derivative to check that the objective is concave:

$$\frac{\partial^2 \Omega(p)}{\partial p^2} = \int_p (-dF^{J-1}(v - p)) dF(v) = - \int_p (J - 1) F^{J-2}(v - p) f(v - p) f(v),$$

which is always negative; so the on-platform profit term is concave. \square

Proof of Proposition 2

This result is implied by Proposition 3.

Proof of Proposition 3

Let the right hand sides of the pricing equations (3) and (4) be

$$\Phi_B(x) = \frac{1 - F(x) + \frac{\lambda J}{1-\lambda} \left(\int_x F^{J-1}(v - x) dF(v) \right)}{f(x)}. \tag{12}$$

and

$$\underline{\Phi}(x) = \frac{1 - F(x)}{f(x)}.$$

respectively. Clearly $\Phi_B(x) \geq \underline{\Phi}(x)$, with inequality holding strictly if $x < 1$ and $\lambda > 0$. Since, by regularity $\underline{\Phi}(x)$ is decreasing, and p_M is a fixed point of $\underline{\Phi}$ and p_B is a fixed point of Φ_B , we must have $p_B \geq p_M$.

To see the first statement, note that $\lambda/(1 - \lambda)$ is increasing in λ , and so the right hand side of the implicit price equation (12), is increasing in λ . It follows that p_B is also increasing in λ . Then the second statement follows from the first and the fact that CS_{off} and CS_{on} are both decreasing in p . Examining Π_{off} , note that

$$\frac{d\Pi_{\text{off}}}{dp} = 1 - F(p) - pf(p) = f(p) \left(\frac{1 - F(p)}{f(p)} - p \right).$$

Since by Proposition 2, $p_B \geq p_M$,

$$\frac{1 - F(p_B)}{f(p_B)} - p_B \leq \frac{1 - F(p_M)}{f(p_M)} - p_M = 0.$$

So since p_B is increasing in λ by the first statement, and Π_{off} is decreasing in p , it follows that Π_{off} is decreasing in λ . For on-platform consumers, Π_{on} is clearly increasing in p , so Π_{on} is also increasing in λ . For the platform revenue, recall that

$$R(p) = \lambda J \left(\int^p \int^v v' dF^{J-1}(v') dF(v) + \int_p \int_{v-p}^v v' dF^{J-1}(v') dF(v) \right).$$

It suffices to show that the parenthesized part is increasing in p , since p is increasing in λ . Taking the derivative of the parenthesized part, we get

$$\begin{aligned} & f(p) \int^p v' dF^{J-1}(v') - f(p) \int^p v' dF^{J-1}(v') + \int_p (v-p) dF^{J-1}(v-p) dF(v) \\ &= \int_p (v-p) dF^{J-1}(v-p) dF(v) > 0. \end{aligned}$$

Hence, the platform revenue is increasing in λ . Finally, the total off-platform welfare per consumer is clearly decreasing in p , and has no other λ dependence, so W_{off} is decreasing in λ . \square

Proof of Proposition 4

Recall the right hand side of the pricing equation (3) is

$$\Phi_B(x) = \frac{1 - F(x) + \frac{\lambda J}{1-\lambda} \left(\int_x F^{J-1}(v-x) dF(v) \right)}{f(x)}.$$

The partial derivative of this expression with respect to J gives

$$\begin{aligned} \frac{\partial \Phi_B}{\partial J} &= \frac{\lambda}{(1-\lambda)f(x)} \left(\int_x (F^{J-1}(v-x) + JF^{J-1}(v-x) \ln F(v-x)) dF(v) \right) \\ &= \frac{\lambda}{(1-\lambda)f(x)} \left(\int_x (1 + J \ln F(v-x)) F^{J-1}(v-x) dF(v) \right). \end{aligned}$$

Since by assumption $J > 1/(\ln F(1 - p_M))$, $1 + J \ln F(v-x) \leq 1 + J \ln F(1 - p_M) < 0$ for $x \geq p_M$. Hence this derivative is negative with respect to J . Since p_B is the fixed point of Φ_B and from Proposition 2 $p_B \geq p_M$, it thus follows that p_B must be decreasing in J .

Since p_B must be decreasing in J , it follows then $CS_{\text{off}}(p_B)$ and $W_{\text{off}}(p_B)$ are increasing in J , since they are decreasing in p and has no other J dependence. Note that W_{on} is equivalently the expected value of the max of J i.i.d random variables distributed as F , and hence is increasing in J . C_{on} is the expected value of an increasing function of v $\max(0, v-p)$, where v is distributed as a max of J i.i.d random variables. Hence the partial derivative of C_{on} with respect to J is positive. Since C_{on} is also decreasing in p and p_B decreases in J , it follows that $C_{\text{on}}(p_B)$ must also be increasing in J . Since CS is a fixed (not J -dependent) linear combination of CS_{off} and CS_{on} and likewise for W , CS and W are both increasing in J . \square

Proof of Proposition 5

By Lemma 1, the firm willing to pay the most for any consumer regardless of off-platform prices is the firm which the consumer has the highest value for; hence, it is not revenue optimal for the platform to exclude any firm from participating. Consider the subgame after all firms have paid the participation fee. By Theorem 1, the pricing condition for off-platform prices is given by (3), and firms bid their true value $\max(v_j, p_B)$. It is then straightforward to see that the maximum participation fee must hold the firm's profit to what they could get from being excluded; hence, it is optimal for the platform to charge transfer fees that make the firm indifferent between joining and not. Since the exclusion profit is given by (5), we are done. \square

Proof of Proposition 6

If the platform's steering policy were inefficient (i.e., $s(v, a) = j$ for a positive measure of consumer values v whose highest value is not for firm j), the platform could instead steer those consumers to their most preferred firms, and receive a higher transfer from the consumer's most preferred firm, since the consumer is worth weakly more to the most preferred firm. Hence it is weakly dominant for the platform to offer each consumer her favorite product. \square

Proof of Lemma 2

Since, by Proposition 6, the platform finds it weakly optimal to make sponsored offers efficiently among participating firms, the platform makes the most revenue from such a steering policy only when all firms accept, since the steering policy is most efficient only when all firms accept (as otherwise, there is loss due to some on-platform consumers being shown a sponsored offer for a firm that is not their favorite). Hence, it is optimal for the platform to set transfers such that all firms are willing to accept. Therefore, the platform must offer each firm the difference between rejecting and best-responding to the resulting steering policy and accepting. So the optimal strategy of the platform must be to reduce the firm's value from rejection as much as possible. Consider the profit firm j could earn by rejecting. Since Proposition 6 implies that the consumers who would have seen j 's product in the sponsored slot now a sponsored offer from the next-best, and the rejecting firm j can only sell via posted price now, the firm j 's profit from rejecting is at least Π_O , the outside option defined in (5). Since offering $p(\cdot, a) = 0$ for $a \neq \bar{1}$ exactly attains this lower bound because firm j only can sell to consumers who value j 's product p more than any other firm, this is an optimal strategy for the platform. \square

Proof of Lemma 3

Suppose the platform chooses a price policy, and the subgame posted price equilibrium resulting from this policy results in posted prices at \bar{p} . If the price policy offered prices larger than \bar{p} , then since the platform weakly prefers sales to occur on-platform, the platform would instead prefer cap its prices at \bar{p} . Hence, the platform anticipates the posted prices set by the firms, and never offers a price larger than the subsequent posted price equilibrium.

Now suppose the platform offers some pricing policy \tilde{p} , and the largest price offered to any value, \hat{p} , is at most the resulting subgame posted price \bar{p} . If the platform is not first-degree

price discriminating up to \hat{p} , then

$$\int \tilde{p}(v) dF^J(v) < \int \min(v, \hat{p}) dF^J(v).$$

Since setting a price cap of 0 earns no profit, the intermediate value theorem implies that there exists a $\hat{p}' < \hat{p}$ such that a first-degree price discriminating policy with cap at \hat{p}' is revenue-equivalent to the original pricing policy. That is, \hat{p}' exists such that

$$\int \tilde{p}(v) dF^J(v) = \int \min(v, \hat{p}') dF^J(v).$$

Since the cap of this alternative pricing policy is lower than \hat{p} , and each firm gets at least as much profit in sales on-platform under this alternative pricing policy if it set a posted price \bar{p} . If $\bar{p} > p_M$, then the firms would also lower off-platform posted prices and gain more surplus, and so the platform could charge a weakly higher transfer for this policy. It could not be the case that $\bar{p} < p_M$, since this would imply that since prices online were capped at $\hat{p} \leq \bar{p}$, some firm would have had an incentive to raise its price to p_M . So the last case to consider is $\bar{p} = p_M$. In this case, to check that this policy is without loss, it suffices to check that firms setting posted prices at p_M is still a subgame equilibrium. Since the marginal incentives for firms to raise or lower posted prices around \bar{p} are unchanged by switching to the price discriminating policy capped at \hat{p}' , it remains to argue that there is no profitable undercutting incentive introduced. But this follows since the first-degree price discriminating policy minimizes the maximum price charged to an on-platform consumer fixing the value of on-platform sales, and so it also minimizes the profit from undercutting deviations. \square

Proof of Theorem 2

We consider two subcases; when $p_C \geq p_M$ and when $p_C < p_M$.

First, suppose $p_C \geq p_M$. Suppose firms $k \neq j$ set off-platform prices p' and consider the best-response problem of firm j , given the pricing policy offered by the platform is capped at \hat{p} . When $p' < \hat{p}$, the profit function takes two forms, depending on whether $p \geq p'$ or $p < p'$. If firm j deviates by raising its posted price to $p \geq p'$, the firm gets consumers poached away if $v_k - p' > v_j - p$, or $v_k > v_j + p' - p$. So the profit function is

$$\frac{1-\lambda}{J} p(1-F(p)) + \lambda \left(\int^{p'} v F^{J-1}(v) dF(v) + \int_{p'}^p v F^{J-1}(p') dF(v) + \int_p p F^{J-1}(v + p' - p) dF(v) \right).$$

The derivative with respect to p in this regime is

$$\begin{aligned} & \frac{1-\lambda}{J} (1 - F(p) - pf(p)) + \\ & \lambda \left(pF^{J-1}(p')f(p) - pF^{J-1}(p')f(p) + \int_p (F^{J-1}(v + p' - p) - p dF^{J-1}(v + p' - p)) dF(v) \right) \\ & = \frac{1-\lambda}{J} (1 - F(p) - pf(p)) + \lambda \left(\int_p (F^{J-1}(v + p' - p) - p dF^{J-1}(v + p' - p)) dF(v) \right). \end{aligned}$$

In the other regime, firm j , by deviating to a price $p < p'$, can poach some consumers whose maximum other value is for some other firm k 's product, but $v_k - p' < v_j - p$. Note that since firm j is undercutting firm k , j can potentially poach consumers whose value $v_k > v_j$. So the profit of the firm from such a deviation is given by

$$\frac{1-\lambda}{J} p(1 - F(p)) + \lambda \left(\int_p^p vF^{J-1}(v)dF(v) + \int_p pF^{J-1}(\min(v + p' - p, 1)) dF(v) \right).$$

The derivative with respect to p is

$$\begin{aligned} & \frac{1-\lambda}{J} (1 - F(p) - pf(p)) + \lambda (pF^{J-1}(p)f(p) - pF^{J-1}(p')f(p)) \\ & + \lambda \int_p (F^{J-1}(\min(v + p' - p, 1)) - p dF^{J-1}(\min(v + p' - p, 1))) dF(v). \end{aligned}$$

As we are interested in symmetric equilibria, we take $p \rightarrow p'$. A quick check confirms that the profit of the firm is both continuous at p' and the left- and right- derivatives match at $p = p'$. Hence, we get the first order condition

$$0 = \frac{1-\lambda}{J} (1 - F(p) - pf(p)) + \lambda \left(\int_p (F^{J-1}(v) - p dF^{J-1}(v)) dF(v) \right) \quad (13)$$

Then it is clear that if $\hat{p} \geq p_M$, and $p_C < \hat{p}$, the resulting posted price subgame equilibrium has firms setting prices p_C .

Now, if $p' \geq \hat{p}$, the left derivative of the best-response profit function is the same as before, but the right derivative changes; specifically, since the platform is already capping the price offers at \hat{p} , any price increase only affects the offline population: that is, the right derivative at $p \rightarrow p'$ is

$$\frac{1-\lambda}{J} (1 - F(p) - pf(p)),$$

which is nonpositive since $p' \geq \hat{p} \geq p_M$. Hence the best response value function of the firms

kinks at p' , but the right-derivative is always negative at the kink. So if $p' \geq p_C$, then the optimal best response is p_C , but if $p' < p_C$, then p' is the best-response. In particular, this implies that for a particular set of subgames $p_M \leq \hat{p} < p_C$ (which turn out to be off-path), there are multiple equilibria in the subgame. That is, any price $p' \in [\hat{p}, p_C]$ is a subgame equilibrium if $p_C \geq \hat{p}$.

However, since the platform is profit maximizing and make a higher transfer profit for more extractive pricing policies (higher $\hat{p} \geq p_M$), if $p_C \geq p_M$, the platform's subgame optimal strategy then is to choose $\hat{p} = p_C$, after which p_C is the unique equilibrium in the posted price subgame.

Now, we turn to the case where $p_C < p_M$. Again, suppose the platform pricing policies cap prices at \hat{p} . Suppose all other firms are pricing at p' . If $p' < \hat{p}$, then the derivative of the best response function (which we analyzed taking $p \rightarrow p'$ above) is

$$\frac{1-\lambda}{J} (1 - F(p) - pf(p)) + \lambda \left(\int_p (F^{J-1}(v) - p dF^{J-1}(v)) dF(v) \right).$$

Note that this is decreasing, and zero at p_C . So p_C is a locally optimal response. However, if $p_M > \hat{p}$, then the best-response profit function has a right-derivative of

$$\frac{1-\lambda}{J} (1 - F(p) - pf(p)),$$

at \hat{p} , which is positive since $\hat{p} < p_M$. This expression also governs the derivative of the best-response on $[\hat{p}, p_M]$; so the best response has a kink at \hat{p} . Hence, the only two potential symmetric equilibria are either p_C or the monopoly price, p_M . Then clearly, if $\hat{p} \geq p_M$, the pricing subgame equilibrium is p_C , and if $\hat{p} \leq p_C$, the pricing subgame equilibrium is p_M .

So it remains to characterize the subgame equilibria if $\hat{p} \in (p_C, p_M)$. Recall that the platform seeks to obtain the maximum transfer from the firms for its service; hence, the platform sets pricing policies to maximize the joint surplus of the platform and firms given the resulting pricing equilibrium. Since the resulting pricing equilibrium is either p_C and \hat{p} , if the platform chooses a price $\hat{p} > p_C$ and the pricing equilibrium is p_C , the joint surplus is

$$(1-\lambda)p_C(1 - F(p_C)) + \int \min(v, p_C) dF^J(v).$$

However, if the platform sets some \hat{p} such that the resulting pricing equilibrium in the

subgame is p_M , the joint surplus is

$$(1 - \lambda)p_M(1 - F(p_M)) + \int \min(v, \hat{p}) dF^J(v).$$

Note that by definition of p_M , $(1 - \lambda)p_C(1 - F(p_C)) < (1 - \lambda)p_M(1 - F(p_M))$, and $\hat{p} > p_C$; hence, it follows that the platform's optimal strategy is to choose the largest possible \hat{p} such that p_M is a pricing subgame equilibrium. (That is, raising \hat{p} increases surplus extraction from on-platform consumers, but the platform cannot raise prices so high that firms want to undercut each other).

That is, suppose the platform capped prices at \hat{p} . The best response profit from undercutting to price p are given by Π_U , and if the firm chooses price p_M , its profit are given by:

$$\Pi_M(\hat{p}) = \frac{1 - \lambda}{J} p_M(1 - F(p_M)) + \lambda \left(\int^{\hat{p}} v F^{J-1}(v) dF(v) + \int_{\hat{p}} \hat{p} F^{J-1}(v) dF(v) \right).$$

Note that $\Pi_U(p_C) < \Pi_M(p_C)$ since the best response p at $\hat{p} = p_C$ is p_C , but that $\Pi_U(p_M) > \Pi_M(p_M)$, since the derivative of the maximand of Π_U is negative at $p = \hat{p} = p_M$. So there exists a largest price $p^* \in [p_C, p_M]$ such that $\Pi_M(p^*) \geq \Pi_U(p^*)$, and it is optimal for the platform to cap prices at p^* , and firms to price at p_M in the subsequent subgame. \square

Proof of Proposition 7

The right hand side of the pricing condition characterizing p_C is

$$\Phi_M(p) = \frac{1 - F(p) + \frac{\lambda J}{1 - \lambda} \left(\int_p (F^{J-1}(v) - p dF^{J-1}(v)) dF(v) \right)}{f(p)}.$$

Note that p_C is the fixed point of Φ_M , and $\Phi_M(p)$ is decreasing in p . Thus, it suffices to show that for some large enough J , $\Phi_M(p_M) < p_M$, as that implies the fixed point of Φ_M is less than p_M .

Recall that p_M satisfies the first order condition

$$1 - F(p_M) - p_M f(p_M) = 0.$$

So

$$\begin{aligned}
\Phi_M(p_M) &= p_M + \frac{\lambda}{(1-\lambda)f(p_M)} \left(\int_{p_M} J (F^{J-1}(v) - p_M) dF^{J-1}(v) dF(v) \right) \\
&= p_M + \frac{\lambda}{(1-\lambda)f(p_M)} \left(\int_{p_M} J \left(\frac{F(v)}{f(v)} - p_M(J-1) \right) F^{J-2}(v) f^2(v) dv \right) \\
&< p_M + \frac{\lambda}{(1-\lambda)f(p_M)} \left(\int_{p_M} J (B - (J-1)p_M) F^{J-2}(v) f(v) dv \right).
\end{aligned}$$

If $J > 1 + B/p_M$, the term in parentheses is negative, so $\Phi_M(p_M) < p_M$, which implies that $p_C < p_M$. \square

Proof of Theorem 3

Once again, we consider the best response problem of a firm given other firms setting price p' .

First, consider firms setting price $p < p'$. Here, since the firm will not poach anyone, firm collects p on all values above p , and the value from all values below p . The firm's profit will be

$$\frac{1-\lambda}{J} p(1-F(p)) + \lambda \left(\int^p v F^{J-1}(v) dF(v) + \int_p p F^{J-1}(v) dF(v) \right).$$

The derivative with respect to p is

$$\begin{aligned}
&\frac{1-\lambda}{J} (1-F(p) - pf(p)) + \lambda \left(p F^{J-1}(p) f(p) - p F^{J-1}(p) f(p) + \int_p F^{J-1}(v) dF(v) \right) \\
&= \frac{1-\lambda}{J} (1-F(p) - pf(p)) + \lambda \left(\int_p F^{J-1}(v) dF(v) \right). \tag{14}
\end{aligned}$$

Now, consider firms setting price $p > p'$. The firm profit function is

$$\begin{aligned}
&\frac{1-\lambda}{J} p(1-F(p)) + \lambda \left(\int^{p'} v F^{J-1}(v) dF(v) + \int_{p'}^p \int^{p'} v dF^{J-1}(v') dF(v) \right. \\
&\quad \left. \int_{p'}^p \int_{p'}^v (v - (v' - p')) dF^{J-1}(v') dF(v) + \int_p \int^{p'+(v-p)} p dF^{J-1}(v') dF(v) \right. \\
&\quad \left. \int_p \int_{p'+(v-p)}^v (v - (v' - p')) dF^{J-1}(v') dF(v) \right).
\end{aligned}$$

The derivative is

$$\begin{aligned}
& \frac{1-\lambda}{J}(1-F(p)-pf(p)) + \lambda \left(\int^{p'} p dF^{J-1}(v') dF(p) + \int_{p'}^p (p-(v'-p')) dF^{J-1}(v') dF(p) \right. \\
& \quad - \int^{p'} p dF^{J-1}(v') dF(p) - \int_p^{p'} p dF^{J-1}(p'+(v-p)) dF(v) \\
& \quad + \int_p \int^{p'+(v-p)} dF^{J-1}(v') dF(v) - \int_{p'}^p (p-(v'-p')) dF^{J-1}(v') dF(p) \\
& \quad \left. + \int_p p dF^{J-1}(p'+(v-p)) dF(v) \right).
\end{aligned}$$

Everything cancels except the first term in the third line, so with a bit of simplification

$$= \frac{1-\lambda}{J}(1-F(p)-pf(p)) + \lambda \left(\int_p F^{J-1}(p'+v-p) dF(v) \right). \quad (15)$$

Comparing (14) and (15), the derivative matches from the left and right at $p = p'$, and so the best-response function is smooth. One can also easily see that $\int_p F^{J-1}(v) dF(v)$ is decreasing in p , so the objective is concave and we can take the first order condition:

$$0 = \frac{1-\lambda}{J}(1-F(p)-pf(p)) + \lambda \int_p F^{J-1}(v) dF(v).$$

Rearranging, we get the implicit characterization of posted prices in (11). □

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